International Journal of Biomedical and Clinical Engineering
Volume 11 • Issue 1

Brain Tumour Detection Through Modified UNet-Based Semantic Segmentation

Mohankrishna Potnuru, GIT, GITAM University (Deemed), India*
B. Suribabu Naick, GIT, GITAM University (Deemed), India

ABSTRACT

The determination of the tumour's extent is a major challenge in brain tumour treatment planning and measurement. Non-invasive magnetic resonance imaging (MRI) has evolved as a first-line diagnostic tool for brain malignancies without the use of ionising radiation. Manually segmenting the extent of a brain tumour from 3D MRI volumes is a time-consuming process that significantly relies on the experience of the operator. As a result, the authors suggested a modified UNet structure based on residual networks that use periodic shuffling at the encoder region of the original UNet and sub-pixel convolution at the decoder section in this research. The proposed UNet was tested on BraTS Challenge 2017 with high-grade glioma (HGG). The model was tested on BraTS 2017 and 2018 datasets. Tumour core (TC), whole tumour (WT), and enhancing core (EC) were the three major labels to be segmented. The test results show that the proposed UNet outperforms the existing techniques.

KEYWORDS

Brain Tumour Detection, Deep-Learning Algorithms, High-Grade Glioma, Semantic Segmentation, UNet Architecture

1. INTRODUCTION

The aberrant cell development in the human brain causes a brain tumour. Malignant brain tumours are becoming more common, which has a significant impact on persons and society (Işın et al., 2016). From literature, manually dividing brain tumours is challenging, much work is being put into developing a system for automatically segmenting brain tumours locations. In the medical field, it is critical to distinguish and interpret malignancies, and a thorough understanding is required. Manually defining brain tumour autonomous regions from MRI data is a perceptual task that takes time and is liable to error (Thaha et al., 2019). The histology glioma is the most common malignant brain tumour, and it has three sub-regions: tumour core (TC), enhancing core (EC), and whole tumour (WT). Gliomas are the most prevalent brain tumours in adults, and there are two forms of glioma: high-grade glioma (HGG) and low-grade glioma (LGG). Most existing brain tumour segmentation research focuses on gliomas which are the most frequent brain tumours in the people. The HGG tumours are cancerous because they develop quickly and cause harm to brain structures. HGG tumour patient needs surgery because they are still unable live for more than two years. Effective treatment of LGG tumours has been shown to improve average lifespan (Forsyth & Ponce, 2011).

DOI: 10.4018/IJBCE.301214 *Corresponding Author

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2. RELATED WORK

Image segmentation is an important part of many visual comprehension systems. It entails dividing an image (or a video frame) into several segments or objects (Naidu et al., 2018). Medical image analysis (e.g., tumour border extraction and organ volume assessment), autonomous vehicles (e.g., accessible surface and pedestrian recognition), surveillance cameras, and virtual reality are just a few of the applications that use segmentation (Forsyth & Ponce, 2011). Whereas, semantic segmentation classify each pixel into respective labels or masks, means it assigns a particular class to all pixels in an image. Deep learning approaches have recently become the illegitimate norm for a variety of medical image processing applications. To segment any image, the existing techniques (Liu et al., 2021) rely on understanding of digital image analysis and mathematics. The computation is simple, and the segmentation generally quick, but the correctness of the segmented not guarantees the carry of much details about the image (Berinde & Ţicală, 2021). By autonomously learning a structure of image features, unsupervised learning algorithms avoid the difficulty of defining and selecting features (Dong et al., 2020). Random forests (RF) and support vector machines (SVM) are perhaps the most effective supervised learning algorithms with discriminative classifiers for effective brain tumour identification (Dabija et al., 2021).

A technique based on deep learning has made significant advancement in the development of image segmentation as of late. The precision of their segmentation has overtaken that of standard tumour segmentation in literature in recent years (Pramod, n.d.). The fully convolutional network (FCN) was the first deep learning structure to properly segment images semantically. It was the first time CNNs were used for mage segmentation. A typical model created by combining deep learning and image processing technology is the convolutional neural network (CNN) (Chiranjeevi & Jena, 2017). It has produced numerous achievements in the field of image analysis and processing as one of the most prominent neural nets in the area of computer vision. The various techniques for brain tumour segmentation are 3-dimensional (3D) and 2-dimensional (2D) segmentation, first one works on CT or MRI images (Song & Montenegro-Marin, 2021) and second one works on slice of CT or MRI images (Kamnitsas et al., 2017). There are little training data or availability of labels for MRI-based 3D segmentation (Pereira et al., 2015), and increasing the quantity of data is challenging. Large network parameters and memory limitations, in particular, make training 3D models difficult. In (Liu et al., 2016) suggested a multipath CNN for segmenting the brain tumour regions on the MRI image's 2D sliced input. They also employed two training processes (phases) to cope with uneven input data classifications. To increase segmentation performance, in paper (Havaei et al., 2017) designed a boundary-aware FCN. Later, Guo et al. (Shen et al., 2017) created Deep Medic, a three-dimensional network that collects low- and mid-feature maps and combines them regionally and abroad via a two-path design. Training data for 2D segmentation, but from the other extreme, are 155 times extra abundant (each 3D-MRI dataset comprises 155 2D sliced information), hence 2D segmentation has subsequently attracted interest (Guo et al., 2021). In paper (Meng et al., 2018) proposed a segmentation methodology in which a cascaded combination of CNN and FCN are used for brain tumour detection. A combination of Recurrent Neural Networks (RNNs) and the long short term memory (LSTM) are also used for image segmentation and are proposed by Järemo in 2021. An early article on semantic segmentation based on de-convolution was published by Noh et al. (Järemo Lawin, 2021). Their model is made up of two parts: a convolutional encoder based on the VGG 16-layer network, and a deconvolutional network that takes the feature map as input and creates a map of pixel-wise posterior probability. Patch-based 2D models, such as Pereira, and FCN-based 2D models, such as U-Net (Noh et al., 2015), are two types of 2D brain tumour segmentation designs. To establish whichever class each identity refers to, the patch-based model classifies nearby patches. Pre-processing, classification using CNNs, and post-processing are the three key processes in the patch-based model pipeline, which takes time and cannot be completed end-to-end. For various types of images, many U-Net postponements have been developed. In (Ronneberger et al., 2015), for example, developed a U-Net design for 3D

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